Abstract Heuristic Dynamic Assignment Based on AIMSUN Microscopic Traffic Simulator

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1 Introduction

This paper discuses one of the most critical aspects of the dynamic simulation of road networks based on a microscopic approach, namely how it performs a heuristic dynamic assignment, the implied route choice models, and whether under certain criteria it can achieve a stochastic user equilibrium. From an analytical point of view dynamic traffic assignment has been usually related to the concept of the dynamic user equilibrium problems. Some of the most successful approaches are inspired on the seminal paper by Friesz et al. 1993, that proposes a dynamic network user equilibrium model which equilibrates the disutilities of the temporal choices. To achieve such equilibrium they take the perspective "that the essential choices available to users of a transportation network –route choice and departure time – occur in time-varying environments and are made rationally", and they conclude with the assumption that these rational choices can only be made if the disutilities of the alternatives are equilibrated. Two main approaches have been used to model these route choices. One based on a generalization of Wardrop's fist principle of static traffic assignment, in which users try to optimize their route based on the current information, this approach describes the evolution of flows when users make route choice decisions based on experienced travel times, and it is usually known as a preventive or en-route assignment, it does not achieve a day-to-day equilibrium pattern, therefore it is considered a dynamic traffic assignment principle and not a true equilibrium. In the above referenced paper Friesz et al. propose an alternative generalization of Wardrop's principle stated in the following terms: *If, at each instant in time, for each* OD *pair, the flow unit costs on utilized paths are identical and equal ti the minimum instantaneous unit path cost, the corresponding flow pattern is said to be in dynamic traffic equilibrium*. This approach, also known as reactive assignment, can be interpreted in terms that could correspond to users having access to a real-time driver information traffic forecasting system or, alternatively, as an approximation to a process by which traveler combine the experienced travel times with conjectures to forecast the temporal variations in flows and travel costs. Friesz et al. 1993 show that under these equilibrium conditions the problem can be formulated as a variational inequality problem. According to (Florian *et al*., 2001), a dynamic traffic assignment model consists of two main components:

1. A method to determining the path dependent flow rates on the paths on the network, and
2. A Dynamic Network Loading method, which determines how these path flows give raise to time-dependent arc volumes, arc travel times and path travel times

In the Dynamic Network Loading, also known as Dynamic Network Flow Propagation, (Cascetta, 2001), “models simulate how the time-varying continuous path flows propagate through the network inducing time-varying in-flows, out-flows and link occupancies”. A wide variety of approaches, from analytical to simulation based, have been proposed. In all them path flows are determined by an approximate solution to the mathematical model for the dynamic equilibrium conditions. The differences between the various referenced approaches lay in the discretization scheme used to solve the Friesz variational inequality problem, and the algorithmic approach to solve the discretized problem (i.e. projection algorithms, successive averages, etc.) and the dynamic network loading mechanism, analytical (Wu *et al*., 1998; Xu *et al*., 1999), or simulation based (Florian et al. 2001).

2 Heuristic Dynamic Traffic Assignment Based on Microscopic Simulation

The assessment by simulation of ITS applications by microscopic simulation requires a route based microscopic simulation paradigm. In this approach, vehicles are input into the network according to the demand data defined as an O/D matrix (preferably time dependent) and they drive along the network following specific paths in order to reach their destination. In the route based simulation new routes are to be calculated periodically during the simulation, and a Route Choice model is needed, when alternative routes are available to determine how the trips are assigned to these routes. The key question that this approach raises is whether this simulation can be interpreted in term of a stochastic heuristic dynamic traffic assignment or not. We propose to investigate the answer to this question in the case of a microscopic simulation using AIMSUN (2003), a route based microscopic simulator (Barceló et al. 1998). This paper is more elaborated version of a previous research reported in Barceló and Casas 2002 and 2004, and Barceló 2004. This process can be interpreted in terms of an heuristic approach to dynamic traffic assignment similar to the one proposed by Florian et al. 2001, consisting on:

1. A method to determining the path dependent flow rates on the paths on the network, based on a Route Choice function, and
2. A Dynamic Network Loading method, which determines how these path flows give raise to time-dependent arc volumes, arc travel times and path travel times, heuristically implemented by microscopic simulation.

The implemented simulation process, Barceló and Casas 2004, based on time dependent routes consists of the following procedure:

Procedure heuristic dynamic assignment

Step 0: Calculate initial shortest path(s) for each O/D pair using the defined initial costs

Step 1: Simulate for a time interval Δt assigning to the available path K_i the fraction of the trips between each O/D pair i for that time interval according to the probabilities $P_k, k\in K$ estimated by the selected route choice model.

Step 2: Update the link cost functions and recalculate shortest paths, with the updated link costs.

Step 3: If there are guided vehicles, or VMS proposing a rerouting, provide the information calculated in 2 to the drivers that are dynamically allowed to reroute on trip.

Step 4: **Case a** (Preventive dynamic assignment)
If all the demand has been assigned then stop. Otherwise go to step 1.
Case b (Reactive dynamic assignment)
If all the demand has been assigned and the convergence criteria holds then stop. Otherwise: Go to step 1 if all the demand has not been assigned yet, or go to step 0 and start a new major iteration

Depending on how the link cost functions are defined, and whether the procedure is applied as one pass method completed when all the demand has been loaded, or it is applied as part of an iterative scheme repeated until certain convergence criterion is satisfied, it corresponds either to a "preventive" or en route dynamic traffic assignment, or to a "reactive" or heuristic equilibrium assignment. In the first case route choice decisions are made for drivers entering the network at a time interval based on the experienced travel times, i.e. the travel times of the previous time interval, and the link cost function is defined in terms of the average link travel times in the previous interval. Alternatively a heuristic approach to equilibrium can be based on repeating the simulation scheme a number of times and defining a link cost function including predictive terms, as proposed by Friesz et al. 1993, (see also Xu et al. 1999).

Route choice based on a day-to-day learning mechanism

In this case the simulation is replicated N times and link costs for each time interval and every replication are stored and thus at iteration *l* of replication j the costs for the remaining *l+1, l+2,…,* L (where L=T/Δt, being T the simulation horizon and Δt the user defined time interval to update paths and path flows) time intervals for the previous j-1 replications can be used in an anticipatory day-to-day learning mechanism to estimate the expected link cost at the current iteration. Let $s_a^{jl}(v)$ be the current cost of link a at iteration *l* of replication j, then the average link costs for the future L-*l* time intervals, based on the experienced link costs for the previous j-1 replications is:

$$\bar{s}_a^{j,l+i}(v)=\frac{1}{j-1}\sum_{m=1}^{j-1}s_a^{m,l+i}(v);\quad i=1,\dots,L-l,(4)$$

The "forecasted" link cost can then be computed as:

$$\tilde{s}_a^{j,l+1}(v)=\sum_{i=0}^{L-l}\alpha_i\bar{s}_a^{j,l+i}(v);\ \ where\ \ \sum_{i=0}^{L-l}\alpha_i=1,\alpha_i\geq 0,\forall i;\ \ are\ \ weighting\ factors\ (5)$$

The resulting cost of path k for the i-th OD pair is

$$\tilde{S}_k(h^{l+1})=\sum_{a\in A}\tilde{s}_a^{j,l+1}(v)\delta_{ak}\qquad(6)$$

where, as usually δ_{ak} is 1 if link a belongs to path k and 0 otherwise. The path costs $\tilde{S}_k\left(h^{l+1}\right)$ are the arguments of the route choice function (logit, C-logit, proportional, user defined, etc.) used at iteration *l+1* to split the demand g_i^{l+1} among the available paths for OD pair i. In the computational experiments discussed in this paper a simplified version consisting of a link cost function defined as:

$$c_{it}^{k+1}=\lambda c_{it}^{k}+(1-\lambda)\tilde{c}_{it}^{k}\qquad(7)$$

Where c_{it}^{k+1} is the cost of using link i at time t at iteration k+1, and c_{it}^{k} and $\tilde{c}_{it}^{k}$ correspond respectively to the expected and experienced link costs at this time interval from previous iterations.

Route Choice Models

In the proposed network loading mechanism based on microscopic simulation vehicles follow paths from their origins in the network to their destinations. So the first step in the simulation process is to assign a path to each vehicle when it enters the network, from its origin to its destination. This assignment, made by a path selection process based on a discrete route choice model, will determine the path flow rates. Given a finite set of alternative paths, the path selection calculates the probability of each available path and then the driver's decision is modeled by randomly selecting an alternative path according to the probabilities assigned to each alternative. Route choice functions represent implicitly a model of user behavior, that emulates the most likely criteria employed by drivers to decide between alternative routes in terms of the user's perceived utility (or, properly speaking, a disutility, or cost in the case of trip decisions) defined in terms of perceived travel times, route lengths, expected traffic conditions along the route, etc. The simulation experiments reported in this paper have been implemented in AIMSUN selecting the Logit, C-Logit and Proportional route choice functions from the default route choice functions available in the simulator. The Multinomial Logit route choice model defines the choice probability P_k of alternative path k, $k \in K_i$, as a function of the difference between the measured utilities of that path and all other alternative paths:

$$P_k = \frac{e^{\theta V_k}}{\sum_{l \in K_i} e^{\theta V_l}} = \frac{1}{1 + \sum_{l \neq k} e^{\theta (V_l - V_k)}} \tag{8}$$

where V_i is the perceived utility for alternative path i (i.e. the opposite of the path cost, or path travel time), and θ is a scale factor that plays a two-fold role, making the decision based on differences between utilities independent of measurement units, and influencing the standard error of the distribution of expected utilities, determining in that way a trend towards utilizing many alternative routes or concentrate in very few routes, becoming in that way the critical parameter to calibrate how the logit route choice model leads to a meaningful selection of routes or not. A drawback reported in using the Logit function is the observed tendency towards route oscillations in the routes used, with the corresponding instability creating a kind of flip-flop process. According to our experience there are two main reasons for this behavior. The properties of the Logit function, and the inability of the Logit function to distinguish between two alternative routes when there is a high degree of overlapping. To avoid this drawback the C-Logit model, (Cascetta *et al.*, 1996; Ben-Akiva and Bierlaire, 1999), has been implemented. In this model, the choice probability P_k, of each alternative path k belonging to the set K_i of available paths connecting the i-th OD pair, is defined by:

$$P_k = \frac{e^{\theta (V_k - CF_k)}}{\sum_{l \in K_i} e^{\theta (V_l - CF_l)}} \tag{9}$$

where V_i is the perceived utility for alternative path i, i.e. the opposite of the path cost, and θ is the scale factor, as in the case of the Logit model. The term CF_k, denoted as 'commonality factor' of path k, is directly proportional to the degree of overlapping of path k with other alternative paths. Thus, highly overlapped paths have a larger CF factor and therefore smaller utility with respect to similar paths. CF_k can be calculated in different ways depending on how the overlapping is defined (i.e. length of common arcs to alternative paths). Other option is the estimation of the choice probability P_k of path k , $k \in K_i$, in terms of a generalization of Kirchoff's laws given by the function

$$P_k = \frac{CP_k^{-\alpha}}{\sum_{l \in K_i} CP_l^{-\alpha}} \quad (11)$$

where CP_l is the cost of path l, α is in this case the parameter whose value has to be calibrated.

3 Computational Results

A set of simulation experiments has been designed and conducted to explore empirically whether the described assignment process, depending on how it is implemented, can be associated to a heuristic realization of a preventive or a reactive dynamic assignment, assuming that a proper selection of a route choice model with the right values for the θ, β, γ or α parameters, depending on the model, should lead to the realization of some equilibrium. A way of measuring the progress towards the equilibrium in an assignment, and therefore qualify the solution, is the relative gap function, Rgap(t) , (Florian et al. 2001, Janson 1991), that estimates at time t the relative difference between the total travel time actually experienced and the total travel time that would have been experienced if all vehicles had the travel time equal to the current shortest path:

$$\text{Rgap}(t) = \frac{\sum_{i \in I} \sum_{k \in K_i} h_k(t)[s_k(t) - u_i(t)]}{\sum_{i \in I} g_i(t) u_i(t)} \quad (6)$$

Where $u_i(t)$ are the travel times on the shortest paths for the i-th OD pair at time interval t, $s_k(t)$ is the travel time on path k connecting the i-th OD pair at time interval t, $h_k(t)$ is the flow on path k at time t, $g_i(t)$ is the demand for the i-th OD pair at time interval t, K_i, is the set of paths for the i-th OD pair, and I is the set of all OD pairs.

A set of computational experiments with models of the networks of: The borough of Amara in the City of san Sebastián in Spain. A model with 365 road sections, 100 nodes and 225 OD pairs; the model of Brunnsviken network in Stockholm. This model has 493 road sections, 260 nodes and 576 OD pairs; Preston City Centre in UK, the model has 1375 road sections, 188 nodes and 1156 OD pairs; the 1,500 Km motorway and highway network of the State of Hessen in Germany, a model with 18,800 road sections, 3,250 nodes, and 60,000 OD pairs

The figures 1, and 2 depict the time evolution of the Rgap(t) function for various Route Choice functions, for the preventive, or en-route version of the assignment procedure, using a K-shortest path algorithm, for the test models of Amara and Brunssviken. In these figures Logit n, corresponds to the above defined Logit function with value n for the shape parameter θ, proportional corresponds to a path probability inversely proportional to the path cost. The expected role of the θ parameter in terms of the Rgaps function becomes evident in the combination of the logit function with the assignment procedure. Improper choices of the parameter values tend to produce a bang-bang effect consequence of the tendency to move most of the flow to the current shortest path, as the oscillations of the Rgap function show, while a more appropriate θ value (θ = 30 in Amara, or θ = 900 in Brunnsviken) not only smooth out significantly the Rgap oscillations but also shows that a path selection with acceptable path costs differences (a 10% in Amara and around a 1% in Brunnsviken.

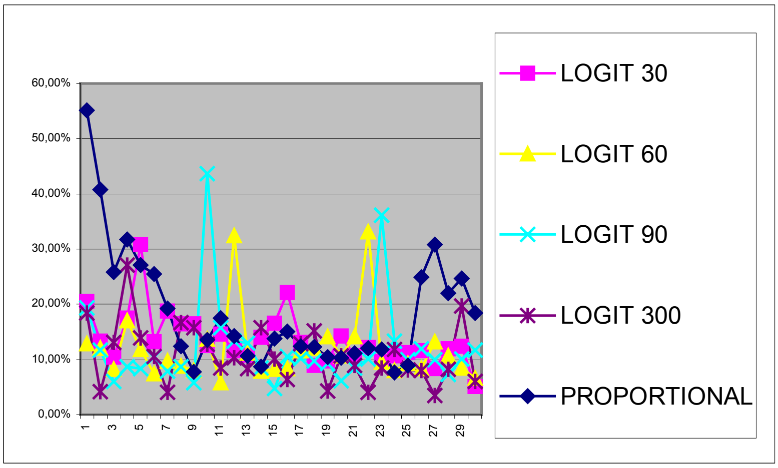

Figure 1. Time evolution of the Rgap fuction for various Route Choice functions for Amara model (Preventive case)

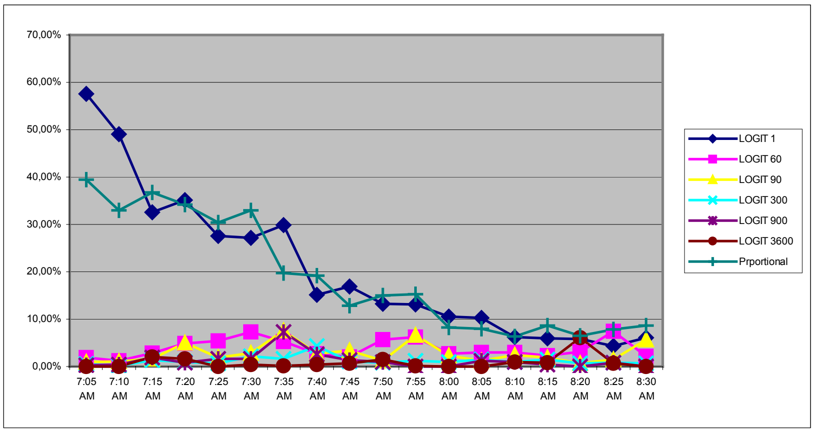

Figure 2. Rgap function for Brunnsviken (Preventive case)

The figures 3 and 4, depict the time evolution of the Rgap function for the same logit route choice function, for the reactive version of he assignment procedure using the costs as defined in (1), at iteration k=20, and λ=0.25, 0.5 and 0.75 respectively, for θ values of 30 in Amara, and 900 in Brunnsviken. Rgap values tend almost to zero, as expected in equilibrium terms, and the variations for the various values of λ show that λ=0.75 is the best.

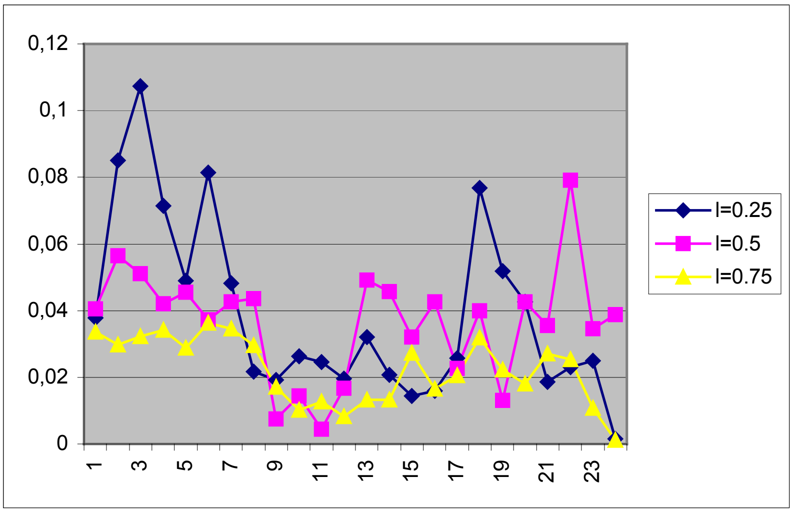

Figure 3. Rgap for Amara (Reactive case)

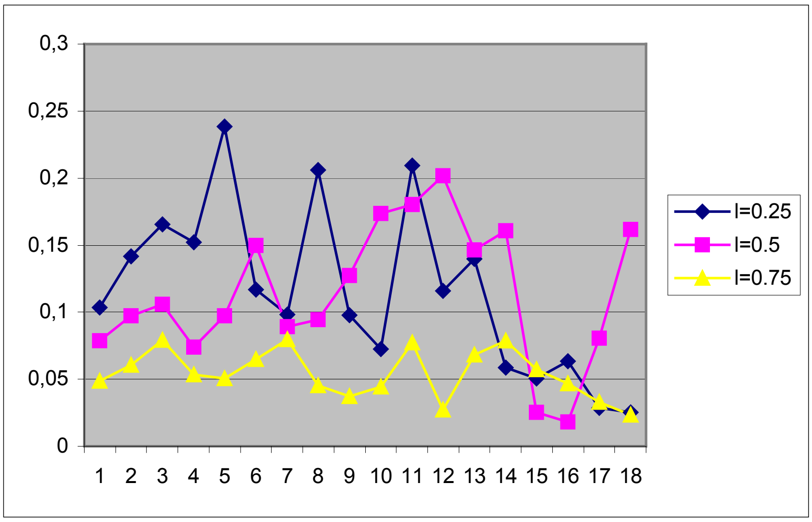

Figure 4. Rgap for Brunnsviken (Reactive case)

4 Conclusions

Assuming_that the “dynamic equilibrium” exists the empirical results show that a proper time varying k-shostest paths calculation, with a suitable definition of link costs, and adequate stochastic route choice functions, using a microscopic network loading mechanism, achieves a network state that can replicate acceptably the observed flows over the simulation horizon, and led to a reasonable set of used paths between OD pairs as the oscillations within a narrow band of the empirical Rgap function indicates, achieving a heuristic dynamic equilibrium.

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